

Ontology and E-Learning

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Abstract. In the last decade the evolution on educational technologies forced an extraordinary interest in new methods for delivering learning content to learners. Distance education represents today an effective way for supporting and sometimes substituting the traditional formative processes, thanks to the technological improvements achieved in the field in recent years. However the role of technology has often been overestimated and on the other hand the amount of information students can obtain from the Internet is huge and they can easily be confused. Teachers can also be disconcerted by this quantity of contents and they are often unable to suggest the correct contents to their students. In the open scientific literature, it is widely recognized that an important factor of this success is related with the capability of customizing the learning process for the specific needs of a given learner. This feature is still far to have been reached and there is a real interest for investigating new approaches and tools to adapt the formative process on specific individual needs. In this scenario, the introduction of ontology formalism can improve the quality of formative process, allowing the introduction of new and effective services. Ontologies can lead to important improvements in the definition of courses knowledge domain, in the generation of adapted learning path and in the assessment phase. This paper provides an initial discussion of the role of ontologies in the context of e-learning. We discuss such improvements related to the introduction of ontologies formalism in the E-Learning field and we present a novel algorithm for ontology building through the use of Bayesian Networks. Finally, we show its application in the assessment process and some experimental results.

1 Introduction

The development of adaptable and intelligent educational systems is widely considered one of the great challenges in scientific research. Among key elements for building advanced training systems, an important role is played by methodologies chosen for knowledge representation. For example, the introduction of standardized tools for defining a set of well-structured concepts can highly improve interoperability and information sharing between complex systems. In literature, a set of concepts and their relationships is commonly called ontology [1]. We can summarize the merits of ontology as following: ontology provides a common vocabulary, and an explication of what has been often left implicit. Obviously the systematization of knowledge and the standardization is the backbone of knowledge within a knowledge-based system. On the other hand a metamodel functionality specifies the concepts and relations among them, which are used as the main building blocks. Ontology is one of the most

effective tools for formalizing the knowledge shared by groups of people. In the E-Learning realm, ontology can easily manage the knowledge domain of a course and allow a more detailed organization and adaptation of the learning path of students [2][3]. Nevertheless, ontology building process is neither trivial nor easy [4]: “building ontologies is difficult, time consuming and expensive” [15]. Several researchers have tried to justify a scientific way for developing ontologies. Perez and Benjamins [30] propose design criteria and a set of principles that have been proved useful in the development of ontologies: Clarity and Objectivity, Completeness, maximum monotonic extensibility, Minimal ontological commitments, Ontological Distinction Principle, Diversification of hierarchies, modularity, minimization of the semantic distance and standardization of names. These principles provide general guidelines for the development of an ontology, which consists of Concepts, Relations, functions/processes, axioms and instances. A “skeletal” methodology for building ontologies has been proposed and tested in [16]. This attempt to formalize the building process through the definition of the following steps:

- Identify purpose
- Build ontology
 - Ontology capture
 - Ontology coding
 - Ontology integration
- Evaluate ontology
- Document ontology

So we can define three sub-steps in the build ontology process [17]:

- Ontology capture: is the identification and definition of key concepts and relationships in the domain of interest that refer to such concepts
- Ontology coding: deals with formalizing such definitions and relationships in some formal language
- Ontology integration: deals with associating key concepts and terms in the ontology with concepts and terms in the ontology with concepts and terms of other ontologies; that is, incorporating concepts and terms from other domains

According to the previous thoughts, the ontology building process is a craft rather than engineering activity [28]. By way of illustration, let us discuss the common case of the use of ontologies for representing the subjects of a course and the relationships among them. When asked to describe their course, teachers regularly provide very intricate ontologies representations, so having to manage that are neither easy to interpret nor to use. Very often, relations among the concepts and their semantic values look more similar to complex puzzles than to useful working tools. It is easy to imagine the consequent difficulty in checking the validity of such descriptions. One way to face the quoted problem is to make available to the user automated tools for building and validating ontologies [5][6]. In literature many tools are available to accomplish most aspects of ontology development. In particular much research has been carried out to investigate the use of ontology to represent data. Source data can be stored in an unstructured, semi-structured, or fully structured format (e.g. textual documents or database schemata). Editing tools such as Protégé 2000 [18] and OIEd [19] have been developed to help users create and edit ontology. However, it is a very difficult and cumbersome task to manually derive ontology from data. Other approaches aim

to tackle this problem through the learning of ontology from free text [20], semi-structured data (e.g., HTML or XML), or structured data from a database [21]. To generate ontology from textual data, text processing techniques such as natural language processing (NLP) combined with association rule mining [22], statistical modeling [23], and clustering [24] have been applied to generate ontology. We have to say that there are not any methodologies to use the huge structured data that are accumulated for a long time. In this paper, we propose an original method for ontology building that can be applied to knowledge domain related to University Curricula. In fact, many E-Learning systems are based on ontologies. Some papers describe an authoring tool based on ontologies to [25] support the development of domain and task ontologies and [26] support and perform (semi) automatic courseware authoring activities. In particular the main assumption of this paper is that in such a context we have a powerful source of evidence: the evaluation tests performed at the end of the course. Usually, teachers design evaluation tests taking into careful account the sequencing and preparatory links of course subjects. So, in our opinion, those tests and the answers given to them by students can be used to individuate the ontology of the course. To this aim, we show how to use Bayesian Networks for easily mapping ontologies and present a novel algorithm for building “lightweight” ontologies through them. Furthermore, we illustrate the application of this method in the assessment phase. Namely, we realized a tool that builds the best assessment strategy according to the information inferred by the analysis of questionnaires. The paper is organized as follows: in Section 2 and 3, we give some details on ontologies and their mapping through Bayesian Networks. In section 4 we describe the proposed approach for the ontologies building process. In section 5 we provide the motivations and the details of assessment tool based on ontology and Bayesian Networks. Finally, in the last section we draw conclusions.

2 Ontology

The concept of ontology is originally taken from philosophy where it means a systematic explanation of being. In recent years, however, this concept has been introduced and used in different contexts, thereby playing a predominant role in knowledge engineering and in artificial intelligence [7]. In 1991, Neches stated that ontology defines the basic terms and relations comprising the vocabulary of a topic area, as well as the rules for combining terms and relations to define extensions to the vocabulary [1]. Later on, Gruber, in the context of knowledge sharing, used the term to refer to an explicit specification of a conceptualization [8]. Mizoguchi summarized the merits of ontology as following: “Ontology provides a common vocabulary, and an explication of what has been often left implicit”. According to Mizoguchi, the systematization of knowledge and the standardization constitutes the backbone of knowledge within a knowledge-based system. He also pointed out that a metamodel functionality specifies the concepts and relations among them, which are used as the main building blocks. Ontology engineering has contributed several interesting aspects to modelling. Maedche and Staab [27] stressed that ontologies could be considered as “metadata schemas providing a controlled vocabulary of concepts”. An inter-

esting clarification of the philosophical term ontology is provided by [29]. This paper summarized several common definitions of ontology and tried to elaborate further the main consideration that ontology is a specification of a conceptualization. According to this approach ontology could be depicted as a philosophical discipline:

- An informal conceptual system
- A formal semantic account
- A specification of a “conceptualization”
- As a representation of a conceptual system via a logical theory
 - characterized by specific formal properties
 - characterized only by its specific purposes
- As the vocabulary used by a logical theory
- As a (meta-level) specification of a logical theory

In the field of computer science, ontology represents a tool useful to the learning processes that are typical of artificial intelligence. In fact, the use of ontologies is rapidly growing thanks to the significant functions they are carrying out in information systems, semantic web and knowledge-based systems. The current attention to ontologies paid by the AI community also arises from its recent interest in content theories, an interest that is greater than the one in mechanism theories. In this regard, Chandrasekaran [7] makes a clear distinction between these theories by asserting that, though mechanisms are important since they are proposed as the secret of making intelligent machines, they can not do much without a good content theory of the domain on which they have to work. Besides, once a good content theory is available, many different mechanisms can be used to implement effective systems, all using essentially the same content. Following this point of view, ontologies are content theories, since their principal contribution consists in identifying specific classes of objects and relations existing in some knowledge domains [9]. Ontological analysis, therefore, clarifies knowledge structures: given a domain, its ontology represents the heart of any knowledge representation system for that domain. Another reason for creating and developing ontology is the possibility of sharing and reusing knowledge domain among people or software agents. In general, ontology is a complex structure made up of a series of elements, each of which is composed of a kind of Relation and a series of related Concepts. An ontology in the context of e-learning means that we admit the presence of an (unspecified) conceptual system, which we may assume to underlie a particular knowledge base. This is the common hypothesis in E-Learning implementations. For example, as far as concerning University Courses, by means of an ontology built by the teacher, it will be possible to describe the knowledge domain, the subjects constituting it, the relations among the various subjects, as well as methodologies and means with which they are presented. These explicit specifications help users to understand what specific terms signify in a given domain [2] and reduce terminological and conceptual ambiguity. The content of an ontology depends both on the amount of information and on the degree of formality that is used to express it. Generally, we distinguish two main types of ontologies: lightweight and heavyweight [3]. A lightweight ontology is a structured representation of knowledge, which ranges from a simple enumeration of terms to a graph or taxonomy where the concepts are arranged in a hierarchy with a simple (specialization, is-a) relationship between them. Heavyweight ontology adds more meaning to this structure by provid-

ing axioms and broader descriptions of the knowledge. In this paper, we will adopt the lightweight approach keeping in mind this definition of ontology: “ontology may take a variety of forms, but it will necessarily include a vocabulary of terms and some specification of their meaning. This includes definitions and an indication of how concepts are inter-related which collectively impose a structure on the domain and constrain the possible interpretations of terms” [10]. In the next section we will show an approach to the representation of ontology by the use of Bayesian networks formalism.

2.1 Ontology and Bayesian Networks

As previously said in this section, we will describe how Bayesian Networks can be used “to map” and “to represent” an ontology. Bayesian Networks have been successfully used to model knowledge under conditions of uncertainty within expert systems, and methods have been developed from data combination and expert system knowledge in order to learn them [11]. Bayesian Networks represent a “hot” topic in the research field; the interested reader can find some interesting good surveys in [12], [13]. In this paper a key role is played by the learning process of Bayesian Networks. It has two important advantages: firstly, it is easy to encode knowledge of an expert and such knowledge can be used to improve learning efficiency and accuracy. Secondly, nodes and arcs of the learned Bayesian network are recognizable links and causal relationships. So users can understand and exploit more easily the knowledge encoded in the representation. A Bayesian network is a graph-based model encoding the joint probability distribution of a set of random variables $X = \{X_1, \dots, X_n\}$. It is composed by:

- A directed acyclic graph S (called structure) where each node is associated with one random variable X_i and each arc represents the conditional dependence among the nodes that it joints
- A set P of local probability distributions, each of which is associated with a random variable X_i and conditioned by the variables corresponding to the source nodes of the arcs entering the node with which X_i is associated. The lack of an arc between two nodes involves conditional independence. On the other hand, the presence of an arc from the node X_i to the node X_j represents that X_i is considered a direct cause of X_j .

Given a structure S and the local probability distributions of each node $p(X_i | \mathbf{Pa}_i)$, where \mathbf{Pa}_i represents the set of parent nodes of X_i , the joint probability distribution $p(\mathbf{X})$ is obtained from: $p(\mathbf{X}) = \prod_{i=1}^n p(X_i | \mathbf{Pa}_i)$ and it is evident that the couple (S, P) encodes $p(\mathbf{X})$ unequivocally (on the hypothesis of conditional independence of the X_i given the \mathbf{Pa}_i) [11].

In order to build a Bayesian Network for a given set of variables, we have to define some arcs from the causal states to the other ones that represent their direct effects obtaining a network that accurately describes the conditional independence relations among the variables. The aim of this paper is the introduction of an algorithm, based on the formalism of the Bayesian networks, able to infer the propaedeutic relationships among different subjects (in other terms the ontology)

belonging to the knowledge domain of a university curricula. The first step of this algorithm is the introduction of a mapping between Ontology and Bayesian Network. In our ontology model, nodes represent the subjects belonging to the knowledge domain (the course) while the arcs mean a propaedeutic relationship among the nodes. We can map this ontology graph in a Bayesian Network in the following way: the Bayesian Network nodes model the subjects belonging to the course Knowledge Domain and the knowledge of subject by students while arcs in the same way mean the propaedeutic relationships among the nodes. Given the previous mapping strategy, our aim is to define the ontology used by teacher in his/her course. Obviously, we must define data type and data set for this approach. As previously said, student's answers to the evaluation tests represent a source of implicit evidence. In fact, teachers through the end-of-course evaluation tests not only assess student's knowledge for every subject, but describe the course ontology and outline the propaedeutic aspects that relate subjects each other. On the basis of these considerations, teachers have designed the final test of the first-level course on Computer Science at the Engineering Faculty of the University of Salerno and the final test of the first-level course on Introduction to Computer Science at the Languages Faculty of the University of Salerno. We must outline that this process was very long and hard for teachers. The result of this process is shown in Figure 1. Each node of the networks has two states and shows the probability that a generic learner knows the subject associated with the same node. We supposed that each node can assume only the following two states (random Bernoullian variable): state 'Yes': complete knowledge of the subject and state 'Not': total ignorance on the subject. The student level of knowledge could be evaluated on the basis of the answers given to the questions (a set of questions is proposed for each subject).

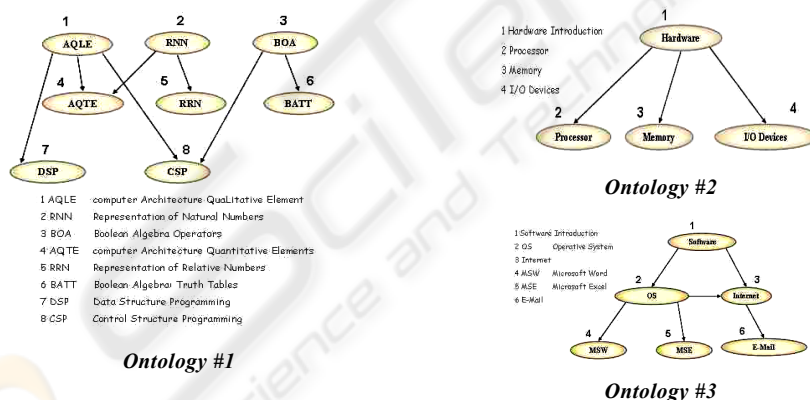


Fig. 1. Proposed ontology for the first-level course on Computer Science (Ontology #1) and Introduction to Computer Science (Ontology #2 and Ontology #3).

3 An Algorithm for Ontology Learning

As previously said, the teacher has difficulties sketching the relationships among the course subjects and their propaedeutic connections. A source of indirect evidence that can be employed for reconstructing “a-posteriori” ontology can be represented by the

end-of-course evaluation tests. On the basis of the ontology presented in Figure 1, some multiple-choice questionnaires have been realized. The previously described graph represents the ontologies, but can also be used as a Bayesian Network for the inference process. The student's level of knowledge is evaluated on the basis of the answers given to the questions. The presence of missing values, in other words the state of some variable can not be observable, has not been foreseen. This hypothesis can be obtained imposing that the student have answer to all the questions and considering a missing answer as a wrong one. Through a process of Bayesian inference conducted on the previously described networks, the candidate ontologies have been learned from data. The inference algorithm used in our experiments is the one called "junction-tree" introduced by Finn V. Jensen in [14]. For the inferential process, we have used data coming from five hundred questionnaires for the first ontology and three hundred questionnaires for the second and third ones. So, we have to estimate the strength of propaedeutic relationship between two arguments after the learning of the network. The presence of an arc between two nodes in the Bayesian network can be interpreted as the existence of a causality relationship between the variables associated to the same nodes. It is important to define a function able to evaluate this strength. For the nodes that belong to a Bayesian network a good dependence indicator is the cross-entropy function so defined:

$$C.E.(A, B) = \sum_{a,b} P(a,b) \log \frac{P(a,b)}{P(a)P(b)}$$

where A and B are nodes of the Bayesian network and a and b are the states of each node. According to cross entropy definition, we can say that A and B are independent if and only if C.E.(A, B) is equal to 0. However, often we do not have the real probability distribution of the full network but only an empirical evaluation of it coming from data analysis. In this sense, it is incorrect to consider as condition of independence C.E.(A,B) = 0 and we can suppose A independent from B when C.E.(A,B) < e, where e > 0 is an arbitrary threshold near to zero. The cross entropy function can also quantify the dependency weight between the nodes. In fact, an high value of C.E.(A,B) means a very strong preparatory relation between the two nodes. In order to suppose that at least the father-child nodes links proposed by the teacher is correct, we submitted the data coming from the questionnaires to statistical tests, typical of Bayesian network structural learning algorithms that are able to establish from them the correct father-child nodes arrangement. This tests result confirmed that the arrangement proposed by teachers is correct. After this validation, we set as input to the Bayesian network the data coming from the questionnaires in order to obtain the probability values associated to the various states of the nodes. With these values we calculated the cross entropy values among all the single states of the net. Namely, the cross entropy has been calculated not only for the arcs proposed by the teacher but also for all the brother nodes.

Figure 2 shows the obtained results. On the left side of the Figure, we can see the cross entropy values for the correct arcs that represent propaedeutic connection between two topics, while on the right side (after the blank column) we can see the cross entropy values for the incorrect arcs. In general, we can say that the arcs designated by teachers show a greater cross entropy values than other arcs so to confirm the teacher ontology design. We want also outline that in the case of ontology #1, an

arc $P(8|6)$ having a cross entropy value in the range of correct arcs is reported. Given that examined data show the existence of a significant value of cross entropy between these nodes the teacher, according to this model, has to refine his original ontology proposal.

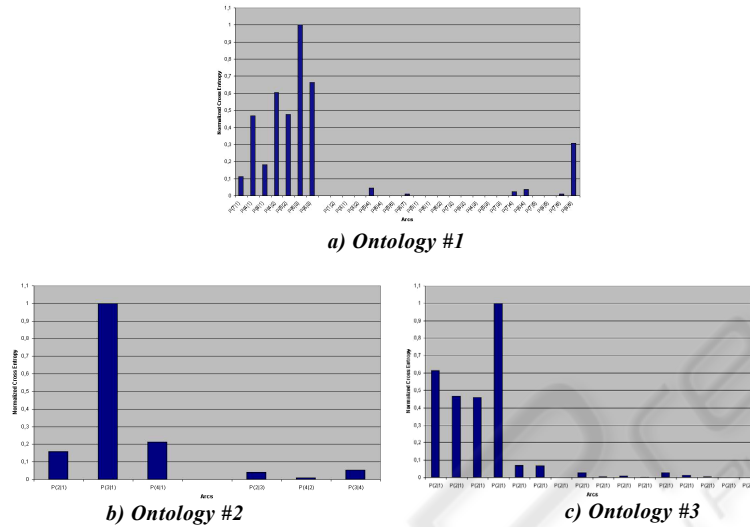


Fig. 2: (a,b,c) Obtained Results on reference set ontologies.

4 An Assessment Tool based on the Ontology Framework

In this section, we will describe in detail the architecture of an assessment tool based on ontology framework previously described. We designed our tool keeping in mind the main needs of students and teachers. From a technological point of view we designed the tool according these constraints: Web based approach - Aesthetic and minimalist design - Flexibility and efficiency of use - Help users recognize, diagnose, and recover from errors. In the first phase of the designing we pointed out the actors of the system and the use cases. We identified three typologies of actors in the system: Administrators, Teachers and Students. Each of these figures has a well defined role and tasks. In particular Administrators can introduce new courses, describe new ontologies and manage the accesses to the tool. Teachers can design the reference ontology, describe the learning objects and the questions linked to the nodes of ontology. Teachers can also manage the reports of every student in order to better supervise the learning process. Students can use tool in three different ways: Exam, Normal test, Bayesian test. In the Exam way our tool arranges a classical final test exam according to the teacher's strategy. In particular teacher can choose the question's number for every subject and the scoring for every question. At the end of the exam the system produces a report analyzing the performance of student in every subject. The normal test approach can be used during some module of the course. In particular it can help student to learn better the various learning objects.

The more interesting service offered by our tool is the Bayesian test. This service makes the most of the matching between ontology and Bayesian network. In fact the first step is the introduction of a mapping strategy between Ontology and Bayesian Network. In our ontology model nodes represent the subjects belonging to the knowledge domain of the course and the arcs mean a preparatory relationship among the nodes. In this way we can map the ontology graph in a Bayesian network in the following way: the nodes of Bayesian Network model the subjects belonging to the course. The states (two: yes and not) of nodes represent the knowledge of student in the subject. The arcs mean the propaedeutic relationships among the nodes. In other words a node of Bayesian network-ontology represents the Knowledge domain of a course and quantizes student's knowledge of this node. First of all the system select a set of questions associated to every network node. At the end of this first phase system, through a Bayesian approach infers what subjects the students knows better than others. In fact through the Bayesian analysis the system can measure the percentage of correct answer in a subject. In particular it can predict the percentage of correct answer to a subject after a correct (or not) answer to questions related to propaedeutic subjects. At this point it can apply various strategies: for example it can select and propose to the student the question with the smaller percentage of correct answer. At the end of Bayesian test a detailed report on the knowledge of student in the various subjects is sent to teacher and to student himself. In particular after the Bayesian test the system proposes to the student some learning object for deepening some subjects. At the same time tool proposes to the teacher a periodic report with the analysis of performances of various students in every subject. In this way teacher can understand easily where students need more help. At the end of Bayesian Test the system updates the user profile of students and builds its new adapted learning path of the full course. The system updates also the values of ontology's links according to the method introduced in this paper.

5 Experimental Results

In order to test the effectiveness of our tool we used it during the course of Introduction to Computer Science at Foreign Literature and Language Faculty of University of Salerno. This course is composed by seven modules: Introduction to PC Architecture, Introduction to Operative System, Microsoft Word, Microsoft Excel, Microsoft Access, Microsoft Power Point, and Internet. The organization of every module and is depicted in figure 3.

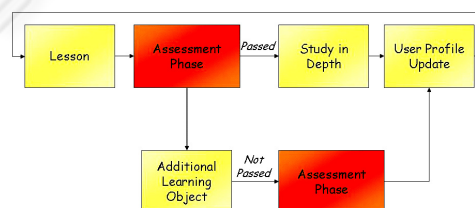


Fig. 3. Organization of every module.

On the basis of the considerations of previous section, teacher designed the reference ontology. Each node of the networks has two states and shows the probability that a generic learner knows the subject associated with the same node. We have supposed that each node can assume only the following two states (random Bernoullian variable): state ‘Yes’: complete knowledge of the subject and state ‘Not’: total ignorance on the subject. The student level of knowledge could be evaluated on the basis of the answers given to the questions (a set of questions is proposed for each subject). At the ends of the course students have to get through a final examination’s test composed by forty questions. The questions belong to every subject of knowledge domain. The number of student’s course was about 50 and at the starting of the course we arranged them in two groups (named blue and red). The first group had a classical support to course activities and used only the normal test approach while the second one used also all functionalities of the tool as didactic support. At the beginning of the course teachers designed every module’s ontology in order to organize the contents and an assessment test. The results are in the table 1. The aim of this test is to allow a first description of student through a metadata structure. In this way teachers can obtain information about the initial knowledge level of students. This information is very useful in order to describe for the first time the student profile. At this point the system organized for the student of red group a support material for every module of course. In particular it selects the most suitable contents through a matching between the metadata of learning objects and the description of the student. As previously said during the course the students of the two groups attended to the lessons and used the virtual teacher tool. In particular students of red group at the end of every module sustained a Bayesian Test. At the end of course students had their final course exam. In the tables we depicted the results:

Table 1. Results of Assessment Tool. The meaning of range are: [0-10]: inadequate, [11-15]: poor progress, [16-20]: adequate, [21-25]: good, [26-30]: very good.

Blue Group		Red Group	
Assessment Test	Students	Assessment Test	Students
0-10	10	0-10	12
11-15	11	11-15	10
16-20	9	16-20	8
21-25	3	21-25	3
26-30	3	26-30	2
Total	36	Total	35

Table 2. Results of Final Test.

Blue Group		Red Group	
Final Test	Students	Final Test	Students
0-10	4	0-10	3
11-15	9	11-15	5
16-20	8	16-20	6
21-25	10	21-25	12
26-30	5	26-30	9
Total	36	Total	35

If we analyze the difference between the assessment and the final exam (table 1 and 2) we can note that the percentage of students that get through the assessment test

is 37% in the red group and 42% in the blue group while in the case of the final examination the percentage is 77% in the red group and 64% in the blue group. We can note as more students of red group get through the final exam and improve their performance respect the assessment test (about 40%). In particular we can note that the students of the blue group have a minor improvement (about 22%) than the students of the red group. At the same time the percentage of red group's students that have a mark in the range 26-30 is higher than in the case of blue group: 26% to 8%. In order to collect more information about the effectiveness of our tool at the end of course we submitted a questionnaire to every student. In the questionnaire we asked the effectiveness of Bayesian test and of learning objects furnished by system at the end of the test. The 87 % of students said that the support of Virtual Teacher tool was very important in the learning process. In particular the 73% of students declared that the supporting learning object helped them in a better knowledge of the various subjects.

6 Conclusions

In this paper, we have presented a method for learning curricula ontologies. In particular, our approach is based on Bayesian networks. Thanks to their characteristics, these networks can be used to model and evaluate the conditional dependencies among the nodes of ontology on the basis of the data obtained from student tests. An experimental evaluation of the proposed method has been performed using real student data. We integrated the proposed method in a tool for the assessment of students during a learning process. This tool is based on the use of ontology and Bayesian Network. In particular through the matching between ontology and Bayesian Network our tool allow an effective tutoring and a better adaptation of learning process to demands of students. The assessment based on Bayesian approach allows as deeper analysis of student's knowledge.

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